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Incorporating ANNs and statistical techniques into achieving process analysis in TFT-LCD manufacturing industry

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ABSTRACT

The ability to improve yield is an important competitiveness determinant for thin-film transistor-liquid crystal displays (TFT-LCD) factories. Until now, few studies were proposed to address the related issues for process analysis in TFT-LCD industry. Therefore, the information (e.g. the domain knowledge or the parameter effect) or the improvement chance hidden from process analysis will be frequently omitted. That is, the yield or yield loss model construction, the critical manufacturing processes (or layers) and the clustering effect based on the abnormal position (or defect) on TFT-LCD glasses will became the important issues to be addressed in TFT-LCD industry. In this study, we proposed an integrated procedure incorporating the data mining techniques, e.g. artificial neural networks (ANNs) and stepwise regression techniques, to achieve the construction of yield loss model, the effect analysis of manufacturing process and the clustering analysis of abnormal position (or it can be viewed as defect) for TFT-LCD products. Besides, an illustrative case owing to TFT-LCD manufacturer at Tainan Science Park in Taiwan will be applied to verifying the rationality and feasibility of our proposed procedure.

1. Introduction

The market for liquid crystal displays (LCDs) is known as a new field with rapid growth in Taiwan. The speculative demand increase has driven capacity expansion, particularly in South Korea, Japan and Taiwan [31]. The price for LCD products is significantly reduced due to both the technology maturity and ample manufacturing capacity. The trend of downward pricing further promotes LCD applications. The primary applications of LCDs include personal digital assistants (PDAs), cellular phones, digital cameras, computers, notebooks, flat panel TVs and various computer game units. During the past several years, the market for LCDs almost has grown at over 20% on an average per annum. LCDs can be divided into three major products including twisted nematic (TN), super-twisted nematic (STN) and thin-film transistor (TFT). The most widely used LCD for high information content display is the thin-film transistor-liquid crystal displays (TFT-LCD) [27].

The manufacturing technology, capital investment and industrial infrastructure are key factors affecting LCD industry competition [16,31,32]. The ability to improve yield for the manufacturing process had been viewed as an important competitiveness determinant for LCD factories due to the significant yield loss ranging from 5% to 25%. This loss is attributed to three major manufacturing sectors: the array, cell and module assembly processes. The yield loss from the cell process is one of the most critical steps. To reduce the yield loss will become an important work for LCD factories. However, no any suitable theories were proposed to discuss the real yield problem. Therefore, the possible improvement opportunity of manufacturing process will be generally missed. In order to survive during the competitive environment, how to mine the useful information from the "know-how" or "domain knowledge" of manufacturing process will be an important issue to all LCD manufacturers. Hence, most manufacturers provide more resources to study such issue via many different approaches, especially for the analysis of the yield model. That is, a flexible model construction in TFT-LCD industry should be another consideration due to the initial development stage of yield or yield loss analysis [11,13,35]. From the systematical viewpoint, several parameters (e.g. the setting of process condition) will significantly affect the result of yield or yield loss model. How to keep the knowledge about the effect on yield or yield loss for those parameters will be also another importance issue. If the relationship among multiple process parameters (e.g. the operating time, pressure, temperature, etc) and yield can be modeled well, information about the feasible parameter settings, the key production process, the important affection effect, the optimum manufacturing solution or the quality improvement may be obtained after performing data analysis via conventional statistical analysis or advanced data mining techniques. Particularly, if the defect status (i.e. the abnormal position) of each manufacturing layer will be chosen

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as the parameters in yield or yield loss model, the critical layer with respect to the yield or yield loss model can be then obtained. Besides, the clustering effect for defect status (i.e. the abnormal position) on each glass will be the subsequent issue to be addressed. From the considerations mentioned above, we will apply the artificial neural networks (ANNs) into the construction of yield or yield loss model and the clustering analysis of abnormal position (or defect) due to ANNs be applied into many manufacturing modeling cases [3,14,17,25,33]. A back-propagation neural network (BPNN) was also applied to set up a quality prediction system for LCD light guide plate moulding [13]. And, Zhang and Zhang [36] proposed a quantitative evaluation based on ANNs to address the issue of mura (a defect status) in TFT-LCD. Hence, in this study, a procedure to achieve the model construction, parameter effect and clustering analysis for yield analysis in TFT-LCD industry was proposed based on integrated intelligent data analysis. In order to verify the rationality and feasibility of our approach, an illustrative example owing to TFT-LCD manufacturer at Tainan Science Park in Taiwan will be also chosen in this study.

2. Background information

2.1. Stepwise model-building technique

Stepwise model-building techniques for regression designs with a single dependent variable had been described in numerous sources [4,6,15,20,21,23,29,34]. The basic procedures of stepwise model-building will involve: (1) identifying an initial model; (2) repeatedly altering the model at the previous step by adding or removing a independent variable (or process parameters) in accordance with the "stepping criteria" and (3) terminating the search when stepping is no longer possible given the stepping criteria, or when a specified maximum number of steps has been reached. The detailed content can be referred to the relating literatures [20,23].

2.2. Backpropagation neural network model

A neural network consists of a number of simple, highly interconnected processing elements (PE) or nodes and is a computational algorithm that processes information by a dynamic response of its processing elements and their connections to external inputs. A neural network can model the non-linear relationship between the system's input and output. The non-linear relationship or the interaction effect among several variables can be kept in the structure of hidden layer of a neural network model. Among the several conventional supervised learning neural models, the BPNN model is frequently used [7,8,12,22] and, therefore, it will be selected herein. A BPNN consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. Detailed descriptions of the algorithm can be found in various sources [22,24]. To develop a backpropagation neural network, the training and testing dataset are firstly collected. The datasets consist of both the input parameters and the resulting output parameters. The back-propagation learning algorithm employs a gradient – or steepest – heuristic that enables a network to self-organize in ways that improve its performance over time. The network first uses the input dataset to produces its own output. This forward pass through the BPNN begins as the input layer receives the input data pattern and passes it to the hidden layer. Each processing element calculates an activation function in first summing the weighted inputs. This sum is then used by an activation function in each node to determine the activity level of the processing node. The output generated by the network is compared to the known target value. If there is no difference, no learning takes place. If a difference exists, the resulting error term is propagated back through the network, using a gradient – or steepest – descent heuristic to minimize the error term by adjusting the connection weights. The detailed content can also be referred to the relating literatures [22,24].

2.3. Fuzzy adaptive resonance theory (fuzzy-ART)

Fuzzy-ART's behavior lends itself well to simple geometrical interpretation owing to an internal representation of category prototypes as hyper-rectangles in the input space. These hyper-rectangles are allowed to overlap each other. Despite these overlaps, the developed categorization is a many-to-one relation and the categories are all mutually exclusive. This is due to the category choice process, by which fuzzy-ART always responds the same way to a familiar input: it recalls the smallest hyper-rectangle containing this input [5]. Hyper-rectangle overlaps have been argued to be an inconvenience if categories are mutually exclusive [26]. Our stance here is that these overlaps can be useful, and we describe a model that exploits them for multiple categorizations. In order to learn intersecting and overlapping categories, a neural network must be capable of repressing previously known categories while it forms new ones. In other words, it must be able to make temporary abstraction of previous knowledge. In the context of categories with various degrees of generality, this can be expressed as two complementary properties: if a neural network with previous knowledge of specific categories can learn new, broader ones, then we shall say that it has the generalization property; if it can do the reverse, then it has the discrimination property. The generalization would allow the learning of the tulips category first, and the flowers category next, whereas discrimination would allow the reverse. In case of fuzzy-ART, increasing the value of a network parameter called vigilance allows formation of new, more specific categories intersecting broad ones that are already known. The network is thus capable of discrimination. However, reducing the same parameter value does not yield generalization. This is due to the predilection of fuzzy-ART for the smallest hyper-rectangle containing the input. To avoid a category proliferation problem that could otherwise occur [19], Carpenter et al. [2] recommend input normalization by a procedure called complement coding. Let a be an M-dimensional vector $(a_1, a_2, \ldots, a_M)$, where $0 \leq a_i \leq 1$. The complement-coded input I is obtained as $I = (a_1, a_2, \ldots, a_M, 1-a_1, 1-a_2, \ldots, 1-a_M) = (a, a_c)$ assign to each category j a vector $w_j = (w_{j1}, w_{j2}, \ldots, w_{j2M})$ of adaptive weights. Each category is initially uncommitted, and its weights are initialized to one. The detailed content about the functionality of fuzzy-ART may be calearly described by Carpenter et al. [2].

3. Proposed approach

Generally, a particular relationship will exist among the input and output variables of a system, e.g. the functional relationship or statistical relationship. From mathematical viewpoint, the logical relationship can be constructed by modeling techniques. Generally, system's output can be viewed as a function of system's input. Ko et al. [12], Su and Hsieh [30], Hsieh, Hsieh & Tong [10], Sanjay et al. [25], Hsieh [8], Mandal and Roy [17], Kuo et al. [14], Chen et al. [3], Vassilopoulos et al. [33] had applied the ANNs to model this logical relationship for many different applications. If the relationship among multiple process parameters (e.g. the operating time, pressure, temperature, etc) and yield can be